

MORE STRUCTURAL HOLES, MORE RISK? NETWORK STRUCTURE AND RISK PERCEPTION AMONG MARIJUANA GROWERS

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ABSTRACT

This study examines the relationship between network structure and risk perceptions. We use self-report data on 359 illicit marijuana growers and their personal co-worker networks. Our results show that growers with more structural holes in their co-worker network perceive higher risk of apprehension from law enforcement. We argue that this result is facilitated by two mechanisms: 1) the amount and quality of information available to growers about risks and detection, which uses guidance from Stafford and Warr's (1993) concept of vicarious deterrence; and, 2) the trust inherent in their network and the growers' self-awareness of their own network position, which relies on Coleman's (1988) and Burt's (2005) ideas of network closure as a protective factor.

Keywords

Marijuana; Cannabis cultivation; Perceptual deterrence; Risks of apprehension; Structural holes; Network closure; Vicarious deterrence

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Introduction

According to deterrence theory, people rationally choose to commit crime by deliberately weighing costs and benefits. Since the inception of the theory, many scholars have argued that the power of deterrence lies in the individual's perception of the certainty, severity, and celerity of punishment (Andenaes, 1974; Geerken & Gove, 1975; Gibbs, 1975; Waldo & Chiricos, 1972; Zimring & Hawkins, 1973). Nagin (1998) summarized this body of survey-based perceptual deterrence studies and concluded that criminality is lower among those who perceive a higher likelihood of apprehension. Thus, it can be said that an inherent part of deterrence theory is perceptual (Paternoster, Saltzman, Waldo, & Chiricos, 1983).

While criminological researchers agree that *perceived risk of apprehension* is an important construct to consider when constructing public policy based on deterrence and the threat of legal sanctions, they have been relatively unsuccessful in isolating its correlates and explaining individual variance (Piquero, Gertz, Bratton, & Loughran, 2012). Variables traditionally considered when examining perceived risk of apprehension include legal sanctions (general deterrence), direct experience with law enforcement (specific deterrence), and offender demographics (Gibbs, 1975). It was not until 1993, when Stafford and Warr reconceptualized traditional deterrence theory, that one's social network was thought to impact risk perception.

Criminological theory is rife with images of social network influence over criminal behavior; concepts like "social bonding, cohesion and control, opportunity structures, diffusion, trust, and peer influence" all convey the importance of an individual's network on their decision

to commit crimes (Papachristos, 2011: 102-102). Deterrence theory was absent this influence until Stafford and Warr integrated deterrence doctrine and social learning theory to form their concept of vicarious deterrence (1993). Vicarious deterrence occurs when an individual bases their judgement about the certainty of legal sanctions on others' punishment or avoidance of punishment for a crime, and on the amount of knowledge one has of their network's criminal activity (Paternoster & Piquero, 1995; Stafford & Warr, 1993).

Qualitative research has provided some guidance in understanding how offenders share information. For example, Patricia Adler (1993) interviewed drug dealers in the US Southwest. She found that dealers use networks of friends and acquaintances to build their business. In reference to vicarious deterrence, these networks share information about perceived risks from police and other dealers. Mohamed and Fritsvold (2010) found similar results, explaining how networks of dealers share information about formal and informal threats. Jacques and Wright (2015) show that communication fueling drug markets operates like a contagion through electronic and in-person interactions. These messages flow through the market from producers, to traffickers, to consumers, and back again.

Research testing the explanatory power of vicarious deterrence has found mixed results. A key explanation for such contradictory results is the difficulty operationalizing vicarious deterrence. Quantitative studies have struggled in translating qualitative results into valid measures. Studies contradicting Stafford and Warr used data obtained by surveying student populations using hypothetical scenarios (Piquero & Paternoster, 1998; Piquero & Pogarsky, 2002; Sitren & Applegate, 2006; 2012) rather than from self-reports of actual criminal activity. The only study to unequivocally support Stafford and Warr's assertions regarding vicarious deterrence and perceived risk used data from self-reports and operationalized vicarious

deterrence as overall knowledge of peers' criminal activity (Paternoster & Piquero, 1995). In addition, previous research has treated individuals independently, instead of being embedded in an interdependent social network; no structural measures of an offender's network have been examined as possible proxies for vicarious deterrence. This omission should be addressed in order to better understand how the structure of one's social network affects an individual's sense of security and perception of risk.

This study fills a gap in the research in three ways. First, we take a new approach to operationalizing vicarious deterrence by using social network variables designed to measure access to information and security and assess their effect on an individual's perception of risk. Second, instead of using student samples, we test vicarious deterrence and risk perceptions using a study population of recently or currently active marijuana growers. Third, we move beyond hypothetical scenarios of criminal experiences and use a self-report survey designed to capture the offender's risk perceptions and personal co-worker network. Addressing these gaps should help clarify the relationship between vicarious deterrence, network structure, and risk perceptions.

Stafford and Warr's Vicarious Deterrence

Empirical support for the effect of vicarious deterrence on perceived certainty of punishment is mixed, at best. Paternoster and Piquero (1995) tested and expanded Stafford and Warr's (1993) original reconceptualization of deterrence theory by studying how knowledge of peers' criminal activity (illicit substance use), which acts as an indirect operationalization of vicarious punishment/avoidance, affects an adolescent's perceived certainty of apprehension for drinking and marijuana use. They found a positive relationship between these two variables,

which supports Stafford and Warr's theory. Piquero and Paternoster (1998) extended this line of inquiry exploring how friends' license suspension or jail time (vicarious punishment), and an estimation of how likely those convicted of drunk driving get the prescribed punishment (vicarious punishment avoidance), effects the respondent's likelihood of drunk driving. Contrary to Stafford and Warr's theorizing, they found vicarious punishment increased criminal intentions and vicarious punishment avoidance decreased criminal intentions. Piquero and Pogarsky (2002) and Sitren and Applegate (2006) studied the effects of friends' arrest (vicarious punishment) and percentage of peers who had driven drunk without detection (vicarious punishment avoidance) on intentions to drive after drinking. Both studies found that vicarious punishment avoidance decreased perceptions of risk, supporting the theory; but vicarious punishment also decreased perceptions of risk, contradicting Stafford and Warr. Replicating this research but extending to an offender population, Sitren and Applegate (2012) surveyed inmates using the same methodology as Piquero and Pogarsky (2002). Their results once again contradicted the theory, showing that vicarious punishment was associated with a lower perceived risk of apprehension.

The contradictory nature of this research leads us to consider other factors that impact how an individual both learns about and interprets risk. We contend that an offender's perception of risk depends upon the interplay between two mechanisms: 1) the amount of information an individual has on their social network's experience with the efficiency or inefficiency of law enforcement (Paternoster & Piquero, 1995), and 2) trust in one's social network. The first mechanism is guided by vicarious deterrence, while the second mechanism is rooted in ideas on network closure and structural holes (Burt, 2005; Coleman, 1988).

Network Structure and Risk Perception

In 1988, Coleman introduced the network closure argument which states that network density can increase social capital by doing two important things: 1) it increases access to accurate information by reducing the number of intermediaries through which communication must pass; and 2) it increases trusts in one's network by enforcing group norms and cooperation. The latter advantage built upon Granovetter's (1981) argument that in situations where individuals face the threat of sanctions, trust is more likely between people who have mutual friends. In 1992, Ron Burt challenged the network closure argument, stating that social capital is created when an individual is able to broker between otherwise disconnected people. He used the term *structural hole* to describe the lack of connection between actors in a network. However, he later acknowledges that the two perspectives actually apply to different problems – dense networks are more adaptable for situations needing collective action and trust, and individuals brokering over structural holes are better able to gain access to specialized groups/knowledge and increase profit. Brass, Butterfield, and Skaggs (1998) elaborated on the trust generated through network closure, proposing that every structural hole in a network presents an opportunity for unethical behavior.

What unites this body of work is the protective features that closed networks have for individuals embedded within them. Lin (2001) conceptualized this idea as the expressive returns of social capital. Expressive returns of social capital have been measured mainly through trust, support (Son & Lin, 2008), social control in the form of discouraging malfeasance (e.g., Colvin, Cullen, & Vander Ven, 2002; Wright & Fitzpatrick, 2006), but also in avoiding detection in a sample of young offenders (Bouchard and Nguyen, 2010). Much like Burt, Lin (1999) argues that closed networks with homophilous ties (contacts with similar characteristics and resources) reinforce the preservation of resources because it increases solidarity and trust whereas extended

networks with heterophilous interactions (contacts with dissimilar characteristics and resources) are more likely to aid in the acquisition of resources (Burt, 1992; Coleman, 1990; Granovetter, 1981; Lin, 1999, 2001).

Interestingly, criminologists working with social network analysis have conflicting views on the benefits of closure in criminal networks. These researchers suggest that criminal networks have to balance the need for efficient business connections and communication with security and secrecy due to the inherently hostile environment in which criminals operate, where the criminal justice system works to inhibit individuals profiting from criminal enterprise (Baker & Faulkner, 1993; Morselli, Giguere & Petit, 2006). This security-efficiency trade-off is moderated by the network's objective and "frequency of action"; networks whose primary purpose is to make money tend to favor efficiency, while networks with more ideological goals or a longer time to act favor security (Morselli et al., 2006: 144). Some research on drug trafficking networks shows that secure networks appear to be higher in network closure (Calderoni et al., 2014; Duijn et al., 2014, Mainas, 2012; Xu & Chen, 2008). However, conflicting research has found that as law enforcement targeting and seizures increase, the network structure reduces density to protect members (Morselli, 2010; Morselli & Petit, 2007; Tenti & Morselli, 2014). None of these studies examined perceptions of risks, the main goal of this study.

Current Study

The current study is the first, to our knowledge, to examine the connection between criminal network structure and perceived risk of apprehension. Specifically, we operationalize vicarious deterrence using social network variables designed to measure access to information

and security and assess their effect on an individual's perception of risk in the context of illicit marijuana growing.

Our guiding research question asks: *Is there a relationship between network structure and risk perceptions?* We argue that the relationship between network structure and risk perception is facilitated by two mechanisms. Neither mechanism predicts that individuals would perceive high risks of detection. After all, by having already decided to participate, our growers believe that risks are low enough as to make it worth their while to get involved. Given this, we first posit that risks perceptions depend on how much information is available to growers about risks and detection, which is itself dependent on how many unique growers one knows. The larger the number of non-redundant contacts, the higher the likelihood of learning about (the otherwise rare instances) in which other growers have been detected. In emphasizing the channels of information from which growers learn about risks, the first mechanism uses guidance from Stafford and Warr's concept of vicarious deterrence (1993).

A second mechanism highlights not how growers actually learn about or acquire new information, but instead focuses on trust and growers' self-awareness of their own network position. Growers embedded in more cohesive, strong tie networks may feel more secure by virtue of their network composition. The more trusted the ties to other growers, the lower the perception that things can/will go wrong. Similarly, the more non-redundant ties, the lower the level of trust, the higher the likelihood that risk perceptions will be adjusted upwards. In framing our hypotheses in this way, we bring our interpretation closer to Coleman's (1988) and Burt's (2005) ideas on network closure as a protective factor, or Lin's research on the benefits of expressive social capital (2001).

It may be that these perceptions do not materialize. If we learned anything from the efficiency/security literature, it is that offenders embedded in less cohesive networks may be at lower risks of detection (Morselli, 2010). Yet, the focus of this study is on the relationship between network structure and perceptions, for a low detection activity in which all respondents decided to participate.

Data and Methods

In order to study the relationship between perceived risk of apprehension and network-based vicarious deterrence we use data from an anonymous international web survey of cannabis cultivators. Online survey methods are particularly well-suited to study this population due to their covert nature (Potter and Chatwin, 2011; Barratt et al., 2012; Barratt et al., 2015). Participants were primarily recruited through advertisements on websites related to marijuana cultivation, college campus advertisements, and advertising in cannabis magazines (for more detail on the recruitment methods see Barratt et al., 2012 and Potter et al., 2015). Former and current growers over the age of 17 were recruited from eleven countries with data collection commencing in early 2012 and ending in 2013 (Barratt et al., 2012; Potter et al., 2015). The core survey (Decorte et. al., 2012) contained 58 questions on growers' marijuana cultivation experiences, reasons for growing, contact with the criminal justice system, and demographics. In addition to this core survey, extra modules were added by researchers from different countries to reflect different research interests. Important to the current paper, growers from Belgium, the Netherlands, and the United States were also asked about their growing networks.

Criminological network literature usually quantifies the security/efficiency trade-off and information exchange at the whole network level – roughly, the extent to which actors are

embedded in social structures and how these structures affect network functioning. However, if we want to understand individual variation in behavior and perception, we need to describe how individuals are embedded in local social structures – ego networks (Freeman, 1982). To capture grower ego networks, each grower was asked to think about the people with whom they had ever worked (partners, bosses, employees, other significant people). They were then asked to list the top five most significant people, using pseudonyms. In order to build alter connections, the respondents were asked whether each of the above named co-workers had worked with one another (co-worker ego network with alter ties).

Sample

We restrict our analyses to individuals residing in Belgium, the Netherlands, and the United States who reported illicitly growing cannabis in the past five years and had networks of two or more alters. This was done for three reasons. First, because sanctions change over time, it is important that the time an individual participated in cultivation is consistent with state or country laws and penalties for cultivation. Second, because we are interested in perceived risk of police apprehension, legal medical growers must be removed as they should perceive no risk from law enforcement for engaging in a legal activity. Finally, because we use two measures of structural holes that are based on alter redundancy, we need to have a minimum ego network size of two. The selection criteria narrowed the original sample in each country substantially (see Table 1 for breakdown of sample by country). Of this sample, there are 359 cases that contain valid data on perceived risk of apprehension. To better understand the ramifications of sample selection, we compared the overall sample (n=1987) to the current sample (n=359) on all of the model variables excluding network variables. The only significant difference was in the number of plants, where the current sample had significantly larger growing operations.

~insert Table 1 about here ~

Dependent variable:

Perceived certainty of arrest: To measure perceived certainty of arrest, subjects were asked “What do you estimate is the risk of you getting caught by police for growing cannabis?” The original variable was coded on a four-item Likert scale from 0=very low risk to 4= very high risk. The distribution of the original variable was negatively skewed, with the following responses: 47.3% = very low risk, 33.9% = low risk, 10.1% high risk, and .3% very high risk. We recoded the responses on a binary scale where 0 = low or very low risk and 1 = high or very high risk. The average perceived certainty rating was 0.13, suggesting generally low risk perceptions (see Table 2 for sample descriptives).

Network-based vicarious deterrence variables:

Measures of structural holes (Burt, 1992) are well-suited to represent vicarious deterrence and network closure. We use three variables to measure structural holes and grower networks:

Effective size: Effective size measures the redundancy of a grower’s network by taking the ego’s degree and subtracting the average degree of the alters. If none of the alters are connected, then the effective size is equal to the ego’s degree. If all of the alters are connected, then the effective size is one. The equation for effective size is:

$$\sum_j \left[1 - \sum p_{iq} m_{jq} \right]$$

Where i = ego, j = alter, and $q \neq i$ or j . $\sum p_{iq} m_{jq}$ calculates the ego network redundancy. The higher the effective size, the more structural holes in a grower’s network, the more the grower acts as a broker, and the more information available to the grower. Effective size ranges from 1

to 5 (due to limiting the co-worker network at 5), with an average of 2.2. The variable is normally distributed.

Efficiency: Efficiency is the effective size normed by the degree of an ego's network. This measure essentially provides the proportion of the grower's network that is non-redundant. A grower can have many structural holes (effective) without having a high proportion of non-redundant ties (efficient), and conversely an actor can be efficient without being effective.

Network size: The third social network variable is a simple measure of the number of alters/co-workers in the grower's network. Network size ranges from 2 to 5, with an average of 3.1 co-workers. The variable is normally distributed.

Constraint: Constraint measures the extent to which the ego is invested in alters who are invested in one another (Burt, 1992). An ego is constrained if their alters are highly connected because they can communicate and broker with one another rather than with the ego. The equation for constraint is:

$$\left(p_{ij} + \sum_q p_{iq} p_{qj} \right)^2$$

Where i = ego, j = alter, and $q \neq i$ or j . Constraint ranges from 0 to 1.125, with an average of 0.65. The variable is normally distributed.

Direct deterrence variables:

We have two variables that tap into direct deterrence:

General country/state punitiveness: Data regarding country/state penalties were gathered from a variety of sources. We used the National Organization for the Reform of Marijuana Laws website (<http://norml.org/>) to gather data for the United States, Belgium, and the Netherlands. These websites detail state/country laws and penalties for marijuana cultivation. We constructed

a measure that captures the general punitiveness of penalties for cultivation by taking the minimum prison sentence. Similar to Nguyen, Malm and Bouchard (2015), we use the minimum prison sentence for cultivation for two main reasons. First, the minimum legislated penalty provides a baseline that we can use to compare across jurisdictions. Second, the majority of the growers who participated in the survey are small-scale growers who are more likely to consider minimum than maximum penalties in their risk calculations. According to deterrence theory, we would expect that growers in states/countries that are more punitive will perceive a higher risk of apprehension.

A total of 44 states are represented in our sample from the United States. The penalties for cannabis cultivation are federally determined in Belgium and the Netherlands; therefore, all growers from these countries were subjected to the same minimum prison sentence for cultivation. Similar to Nguyen et al., (2015) and Ouellet, Bouchard and Malm (2016), the punitiveness variable is represented by the minimum number of days of incarceration for a cultivation offense and ranged from 0 days (Belgium and the Netherlands) to approximately 7,300 days (Kansas) for a cultivation offense. While this variable is positively skewed, no transformation was conducted since there is no assumption about normality on independent variables in binary logistic regression modeling.

Police contact: Research shows that an offender's perception of the risk is affected by their arrest experiences (Anwar and Loughran, 2011). Therefore, we include a binary measure to indicate whether or not an individual self-reported ever being arrested for marijuana cultivation. This number was relatively low, with only approximately 11% of our sample reporting contact with the police for cultivation.

Control variables:

We include a number of control variables to account for the grower's cultivation experience and demographic characteristics.

Number of plants: Since research shows a positive relationship between cultivation size and the risk of detection (Bouchard, 2007), it is important to control for the average number of plants per crop. We hypothesize that growers would perceive a greater risk of apprehension the larger their cultivation site; however, not all research supports this hypothesis (Nguyen et al., 2015). The average number of plants is 10.5, with a median of 5 plants. While this variable is positively skewed, no transformation was conducted since there is no assumption about normality on independent variables in binary logistic regression modeling.

Experience: In order to control for a grower's skill in cultivation, we control for the amount of experience they have with cannabis cultivation (Bouchard and Nguyen 2010; Nguyen and Bouchard, 2013). Subjects were asked how many crops of marijuana he/she has grown thus far. Our sample, on average, has grown 2.5 crops at the time of the survey was conducted.

Type of site: Research has shown that indoor sites are less susceptible to detection than outdoor operations (National Drug Intelligence Center, 2009); therefore, we control for whether the site was indoor with a binary indicator where 1= indoor and 0= outdoor or both indoor and outdoor. The majority of growers in our sample had indoor sites (54%).

Age: The average age of subjects in our sample is approximately 28 years.

Gender: Males in our sample were coded = 1 and females = 0. Approximately 88% of our sample is male.

~insert Table 2 about here ~

Analytic plan:

Our control variables contained few missing values and in order to avoid data loss due to listwise deletion, we estimated models using multiple imputation with SPSS. The variable with the most missing values was number of plants, which had 12 cases with missing values (approximately 3%).

First, we examine the bivariate relationship between all our variables. Due to skew and presence of outliers, Spearman's rho is calculated for cultivation severity, number of plants, and experience. Pearson's product-moment correlation coefficients and point biserial correlations are calculated where appropriate. Second, we run a series of seven nested logistic regression models. The first model tests the effect of control variables on perceived risk. The next model includes the two variables measuring direct deterrence and the controls. The next four models measure the effect of vicarious deterrence on perceived risk, beginning with network size and successively adding each of the structural hole variables. Finally, we run the complete model with all of the explanatory variables, accounting for the control variables.

Results

As shown in the correlation matrix (Table 3), our dependent variable, perceived certainty of apprehension, is moderately positively correlated with the social network-based vicarious deterrence variables effective size ($r_{pb}=.190, p<.01$), efficiency ($r_{pb}=.112, p<.05$), and constraint ($r_{pb}=-.168, p<.01$), but not network size. This result is particularly interesting considering both effective size and constraint have a moderate to strong correlation with network size ($r=.595, p<.01$; $r=-.461, p<.01$ respectively). This supports using four separate social network indicators in the statistical models. Expectedly, the three structural hole variables are highly intercorrelated. Of notable concern is the strong correlation ($r=-.784, p<.01$) between effective size and

constraint; however, we decided to keep both variables in the model based on theoretical and published precedent (Burt, 1992). As for the direct deterrence variables, perceived certainty of apprehension is not correlated with cultivation severity or police contact. Looking at our control variables, perceived certainty is positively related to number of plants ($r_s=.169, p<.01$), experience ($r_s=.144, p<.01$), and age ($r_{pb}=.138, p<.05$).

Some interesting inter-correlations include the positive relationship between effective size and number of plants ($r_s=.126, p<.05$) and experience ($r_s=.147, p<.01$) suggesting that larger, more experienced growers have more structural holes in their network. It also appears that growers with higher efficiency are also more likely to grow indoors ($r_{pb}=.127, p<.05$). Supporting Burt's (1992) theory of structural holes, growers who are less constrained appear to have larger grows ($r_s=-.113, p<.05$) and more experience ($r_s=-.125, p<.05$). Perhaps not surprisingly, growers with larger co-worker networks have more experience ($r_s=.128, p<.05$). More unexpected is the finding that growers residing in areas with higher sanctions have larger co-worker networks ($r_s=.104, p<.05$) larger operations ($r_s=.285, p<.01$), more experience ($r_s=.112, p<.05$), and are more likely to grow indoors ($r_s=.206, p<.01$). The correlations between police contact and control variables are not unexpected - growers who have been in contact with the police due to their cultivation activity have larger operations ($r_s=.171, p<.01$), more experience ($r_s=.216, p<.01$) and are older ($r_{pb}=.170, p<.01$).

~insert Table 3 about here ~

Table 4 shows the binary logistic regression results for perceived threat of apprehension. Model 1 includes only the control variables. Interestingly, the size of a grower's network is

negatively associated with perceived risk. Growing indoors is also negatively associated with perceived risk. Model 2 examines the effect of direct deterrence on perceived risk. Neither sanction severity nor contact with police appear to be associated with perceived risk. However, the model does show growers with more experience have higher risk perceptions.

Models 3 through 6 measure the effect of vicarious deterrence on perceived risk, beginning with network size and successively adding each of the structural hole variables. Including just network size and control variables, Model 3 shows the only significant predictor of perceived risk to be experience. Once we include the other three structural hole variables in Models 4 through 6, we get stable results. Each of these models show network size, effective size, experience, and growing indoors as significant predictors. Growers who perceive higher risk of apprehension have smaller networks with larger effective size (more structural holes). These growers are also more experienced and are less likely to grow indoors.

Model 7 includes all of our network-based vicarious deterrence variables, direct deterrence variables, and our control variables. Effective size and network size remain significant and in the previously stated directions. One of our control variables remains a significant predictor of perceived risk: experience with growing. Respondents who had more experience with growing were more likely to perceive higher risks of apprehension. Network efficiency, constraint, both direct deterrence measures, average number of plants, growing indoors, and demographic characteristics of the grower are not associated with perceived risks of apprehension. The Cox & Snell pseudo- R^2 for the complete model is .143, indicating a relatively robust fit.

In sum, interpretation of the log odds results from the logistic regression analyses indicate that network-based vicarious deterrence has a significant effect on perceived risk. For every

additional structural hole in a grower's network, the odds of perceiving high risk of apprehension increases by 226%. This result contrasts with the finding that a general increase of one individual in the grower's network reduces perceived risk by 53%. This result holds true controlling for direct deterrence, site characteristics, and respondent demographics.

~ Table 4 about here ~

Discussion

This research extends the application of network-based vicarious deterrence to the perception of risk. The findings show that among illicit cannabis cultivators who work with two or more individuals, those with more structural holes in their networks perceive a greater risk of apprehension by law enforcement. The more non-redundant contacts in a network, the higher the likelihood of perceiving higher risks of detection from cultivation activities. The analyses revealed that this is not merely a "size" effect. Instead, the final model showed a negative and significant association between pure network size and perceived risks once both measures were accounted for. These combined findings support the hypotheses laid out in the front end of the study and highlight the importance of tie redundancy and trust when examining perceived risk.

It was proposed that growers who bridge more structural holes have access to more growers and as such, more information on risks and detection in the industry. The negative association between network size and risk perception emphasizes how simple access to growers is not as important as the brokerage role; this supports Granovetter's (1981) work on weak ties and Burt's (1992) discussion of structural holes. They are also, by definition, embedded in networks where trust levels are assumed to be lower than other, strong tie networks. Growers in

large, cohesive networks appear to feel more protected than growers in large networks of weak ties; this supports the network closure argument (Burt, 2005; Coleman, 1988; Lin, 2001). While we offer support for both mechanisms, the data are not amenable to testing whether the findings are driven by information channels where growers learn about risks (Stafford and Warr, 1993), or whether this is merely an issue of network structure and trust (Coleman, 1988; Burt, 2005; Lin, 2001), or a combination of the two. Future research should tease apart these two mechanisms in an effort to better learn how offender's experience perceptual deterrence within social networks, a fruitful avenue to broaden the boundaries (and explanatory power) of deterrence theory.

While not a central focus of this study, it is worth noting that the findings for direct deterrence appear to contradict deterrence theory. Neither severity of sentencing or direct police contact was associated with risk perceptions in model 2 or the complete model. Since we restrict our sample to active growers who were not initially deterred, it is possible that the direct effect of perceptual deterrence might act as a gatekeeper of sorts. People who risk growing marijuana in areas with high sanctions likely see themselves as more skillful and better able to evade authorities. Personality traits such as impulsivity, which we are not able to control using this data, may also act as an intervening factor.

The finding that increased cultivation experience leads to an increased perception of risk might at first seem contradictory, as more skill should imbue the grower with a sense of confidence and ability to successfully evade authorities. At the same time, experienced growers are also more likely to have had contacts with the police, and to bridge more structural holes, both which could have led to perception of risks be adjusted upwards. With experience also

comes the knowledge of all the ways in which things can go wrong, including the potential for detection (Bouchard and Nguyen, 2011).

This study has three notable limitations. First, in interpreting these results, it should be kept in mind that the analysis suffered from a temporal issue. It is conceivable that perceptions are formed first, independent of the network, and that the nature of such perceptions structure the type of network in which individuals are embedded. Second, it is not possible to generalize our findings to other illicit networks, or even other groups of marijuana growers. Growers who are willing to respond to online surveys may be selectively different from those who do not respond. Further, self-selection bias is likely to have implications on the internal validity of our results. Our sample consisted mostly of small-scale growers who were willing to participate in an anonymous online survey and this would most likely reduce perceptions of risk. It is likely that growers with a high risk perception would be deterred from completing an online survey. Future research should gather information through different sampling strategies targeting growers with more commercial motivations. Finally, the network generator limited co-workers to a maximum of five. This was done in order to maximize response rate and minimize confusion. However, it is possible that this boundary artificially reduced the number of co-workers and variance in the structural hole measures. That said, the mean network size (3.1) and standard deviation (1.23) do not indicate that this would be a major issue for this type of sample.

Conclusion

This study highlights the importance of social network structure on risk perceptions. Using a self-report survey of marijuana cultivators, we show that growers with more structural holes in their co-worker network perceive higher risks of apprehension from law enforcement.

Specifically, our research suggests growers who broker over structural holes have access to more information on risks and detection in the industry. This likely increases the low risk perception that initiated their criminal activity. These growers are also embedded in networks with lower trust – growers in large, cohesive networks appear to accurately feel more protected than growers in large networks of weak ties. These results further support the extension of “networked criminology” to the study of perceptual deterrence and risks specifically, and to self-report surveys more generally.

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Table 1. Breakdown of number of respondents by sample for each country

Country	Original Sample	Network Sample	Ego Network >2	Ego Network >2 and Perceived Risk
Belgium	1065	278	174	170
Netherlands	277	66	37	35
United States	645	216	155	154
TOTAL (n)	1987	560	366	359

Table 2. Descriptives of sample (n=366)

Variable	n	Mean	Median	Standard Deviation	Minimum	Maximum
Perceived certainty of apprehension	359	0.13	0	--	0	1
Vicarious deterrence:						
Network size	366	3.10	3.0	1.23	2	5
Effective size	366	2.22	2.00	1.20	1.0	5.0
Efficiency	366	0.80	0.78	0.76	0.2	1
Constraint	366	0.65	0.53	0.29	0	1.125
Direct deterrence:						
Cultivation severity (mandatory minimum sentence in days)	366	372.77	0.00	984.01	0.0	7300
Police contacts	352	0.11	0	--	0	1
Controls :						
Number of plants	347	10.51	5.00	17.50	1	101*
Experience (number of crops)**	358	2.49	2.00	1.58	0	6(50+)
Indoor	355	0.54	1	--	0	1
Age	347	28.65	25.00	9.91	18	65
Male	350	0.88	1	--	0	1

Non-imputed data

* variable truncated at 101 or more plants per crop

**grouped variable

Table 3. Correlation¹ matrix of variables (n=359)

	1	2	3	4	5	6	7	8	9	10	11	12
1. Perceived certainty	1.000											
2. Network size	0.029	1.000										
3. Effective size	0.190**	0.595**	1.000									
4. Efficiency	0.112*	0.079	0.356**	1.000								
5. Constraint	-0.168**	-0.461**	-0.784**	-0.320**	1.000							
6. Cultivation severity	-0.088	0.104*	0.109*	0.102	-0.133*	1.000						
7. Police contact	0.076	0.023	-0.017	0.019	0.054	0.070	1.000					
8. Number of plants	0.169**	0.084	-0.126*	0.088	-0.113*	0.285**	0.171**	1.000				
9. Experience	0.144**	0.128*	0.147**	0.067	-0.125*	0.112*	0.216*	0.464**	1.000			
10. Indoor	-0.060	0.028	0.087	0.127*	-0.082	0.206**	-0.035	0.143*	0.140**	1.000		
11. Age	0.138*	0.013	0.040	0.068	-0.051	-0.041	-0.170**	0.229**	0.386**	-0.024	1.000	
12. Male	-0.020	-0.005	-0.001	0.031	-0.008	0.003	0.072	0.074	0.047	-0.003	-0.099	1.000

Imputed data

¹ Due to skew and presence of outliers, Spearman's rho calculated for cultivation severity, number of plants, and experience. Otherwise, Pearson's and point biserial correlations reported where appropriate.

* p< .05

**p<.01

Table 4. Binary Logistic Regression (n=359)

Variable	Model 1 (Control) Odds (95% CI)	Model 2 (Direct) Odds (95% CI)	Model 3 Odds (95% CI)	Model 4 Odds (95% CI)	Model 5 Odds (95% CI)	Model 6 Odds (95% CI)	Model 7 (Full) Odds (95% CI)
Vicarious							
deterrence:							
Network size			0.882(0.64; 1.22)	0.445(0.25; 0.79)**	0.448(0.25; 0.79)**	0.469(0.26; 0.84)*	0.440(0.24; 0.82)**
Effective size				2.625(1.48; 4.65)**	2.582(1.44; 4.63)**	2.257(1.04; 4.91)*	2.558(1.10; 5.98)*
Efficiency					0.790(0.73; 1.51)	1.052(0.73; 1.51)	0.977(0.67; 1.43)
Constraint						0.576(0.06; 5.72)	0.784(0.06; 1.43)
Direct							
deterrence:							
Cultivation		0.999(0.99; 1.00)					.999(0.99; 1.00)
severity							
Police contacts		1.128(0.39; 0.27)					1.443(0.48; 4.37)
Controls:							
# of plants	1.010(0.99; 1.03)*	1.010(0.99; 1.03)	1.004(0.98; 1.03)	2.296(0.82; 6.45)	2.289(0.82; 6.43)	2.319(0.82; 6.54)	2.38(0.83; 6.85)
Experience	1.526(1.11; 2.10)	1.365(1.02; 1.83)*	1.574(1.13; 2.20)**	1.442(1.04; 1.99)*	1.438(1.04; 1.99)*	1.441(1.04; 2.00)*	1.474(1.05; 2.06)*
Indoor	.412(0.17; 1.00)*	0.520(0.22; 1.22)	.515(0.21; 1.25)	0.385(0.17; 0.86)*	0.380(0.17; 0.85)*	0.372(0.17; 0.84)*	0.544(0.23; 1.27)
Age	1.018(0.98; 1.06)	1.019(0.98; 1.06)	1.019(0.98; 1.06)	1.015(0.98; 1.05)	1.014(0.98; 1.05)	1.014(0.98; 1.05)	1.012(0.97; 1.05)
Male	.700(0.23; 2.18)	0.790(0.26; 2.41)	.701(0.22; 2.20)	0.724(0.23; 2.24)	0.716(0.23; 2.22)	0.709(0.23; 2.20)	0.666(0.21; 2.10)
Wald Chi ²	19.917***	14.804***	9.344***	11.965***	11.949**	3.578***	3.163*
Cox & Snell R ²	.113	.096	.140	.120	.120	.121	.143
Constant	.026	.035	.037	.035	.036	.061	-2.785

*p<.05

**p<.01

***p<.001

Imputed data